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How Does Climate Change Influence the Economic Value of Ecosystem Services in Savanna Rangelands?☆

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ABSTRACT

Savanna rangelands provide essential ecosystem services to people. Intense land-use and climate change may degrade ecosystems and influence the provision of ecosystem services. Complex dynamic vegetation models can simulate future vegetation and how vegetation may interact with land-use. Yet, identification of best-practice management directives in the face of climate change is challenging and requires consideration of socio-economic aspects. Here, we developed an economic model to describe the value of key ecosystem services, namely fuelwood harvesting and livestock, and coupled it with aDGVM, a vegetation model for tropical ecosystems. We used simulation optimization to identify land-use strategies that maximize economic value to stakeholders in the planning horizon until 2050, and compared it to realistic land-use intensities. We found that realistic intensities exceed optimal intensities, indicating the tragedy of the commons and external stress factors, prevalent in many rural savanna rangelands. We show that a reduction in fuelwood harvesting until 2050 allows vegetation to recover but that recovery is slow. We conclude that strong governance is important in rural savanna rangelands to ensure sustainable use of resources under future climate conditions. The coupled ecological-economic model can serve as tool to develop sustainable land-use strategies in complex socio-ecological systems globally.

1. Introduction

Savanna rangelands provide people with important ecosystem services. Two major ecosystem services are livestock production and supply of fuelwood. Livestock is owned for multiple purposes, including the production of milk, meat and manure, use for labor, as a status symbol or for other cultural purposes (Shackleton et al., 2005). Fuelwood is still the most important energy source for cooking and heating in many rural areas of sub-Saharan Africa (Matsika et al., 2013). In these areas, ecosystem services are typically required for subsistence, but they can also generate economic income for farmers who are selling products produced from ecosystem services.

Many savanna rangelands are under heavy pressure due to intensification of land-use, expansion of settlements, as well as climate change (Niang et al., 2014). The main drivers of these processes are human activities and the increasing human population size in savanna rangelands that lead to increasing demand for ecosystem services and concomitantly enforced pressure on the land (Niang et al., 2014). Land-use intensities often exceed the thresholds of sustainable ecosystem use and lead to potentially irreversible changes in biodiversity, vegetation states and soil conditions. Land-use therefore may lead to degraded ecosystem states that are unsuitable for the future provision of key ecosystem services. Overexploitation of resources is particularly critical in communal lands and reasons are manifold. They include external stress factors such as expansion of other land-use forms (e.g. agriculture or game reserves, McPeak et al., 2015; Ruttan and Borgerhoff Mulder, 1999), changes in property rights (Lesorogol, 2008; Hogg, 1990) or a lack of large-scale management policies for a region. Internal stresses include stakeholders that may exploit resources for individual benefit at the expense of other members of the community ("tragedy of the commons", Hardin, 1968; Gordon, 1954), although access to pastures and resource use are often regulated within communities (Ruttan and

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Borgerhoff Mulder, 1999; Galaty, 1994).

Fuelwood harvesting and livestock have impacts on vegetation structure and dynamics. Fuelwood harvesting may alter tree population structure by increasing the number of small and tall trees while reducing the number of trees in size classes suitable as fuelwood (Twine and Holdo, 2016; Mograbi et al., 2015). Although fuelwood harvesting can lead to increased mortality of affected plants (Luoga et al., 2004), many savanna tree species are highly adapted to loss of aboveground biomass to fires, browsing and wood harvesting and can re-sprout from the roots to regenerate. Changes in vegetation structure often imply reduced supply of fuelwood, even though total woody biomass or density may increase (Mograbi et al., 2015). From the perspective of fuelwood collectors, such a system state can be considered as degraded and such changes in the woody plant community may result in a fuelwood crisis (Wessels et al., 2013).

Livestock reduces grass biomass and thereby shifts the competitive balance between grasses and trees towards tree dominance and shrub encroachment (Midgley and Bond, 2015). Shrub encroachment has been reported for many savanna regions of the world (Stevens et al., 2017) and empirical evidence indicates reduced grazing capacity and cattle production in these areas (Mugasi et al., 2000; Angassa, 2014). Many shrub species are unpalatable and well-protected against herbivory by cattle, for example by thorns, tannins or by their architecture (Charles-Dominique et al., 2017). In addition, the dense vegetation structure of encroached areas often limits the mobility of animals. Krätli et al. (2013) highlight the importance of pastures for food security and the economic value, and argue that a high potential for further developments lies in these systems, in particular under future climate conditions.

The complex network of interactions between humans, livestock and vegetation is further influenced by climate change. More frequent and severe droughts are projected for many arid and semi-arid zones, which may accelerate the loss of indispensable ecosystem services, ecosystem functions and biodiversity (Niang et al., 2014). Increases in the atmospheric CO_2 concentration may fertilize woody vegetation and accelerate shrub encroachment (Wigley et al., 2010; Higgins and Scheiter, 2012; Midgley and Bond, 2015).

Changes in the resource base due to land-use or climate change require adjustments of land-use practices in rangelands to maintain subsistence and to ensure sustained provision of ecosystem services. Land-use practices are further challenged by changes in the socio-ecological context and in political decisions that modify the option space for land-use. For example, access to electricity in rural South Africa is rapidly increasing with approximately 55% of the rural households having access to electricity (Pereira et al., 2011). Access to electricity in turn influences the energy mix of households for cooking or heating and may allow recovery of vegetation during the next decades due to a reduced fuelwood demand. Nonetheless, 54% of rural households keep using wood as main energy source for cooking and heating (Serwadda-Luwaga and Shabalala, 2002; Madubansi and Shackleton, 2006), especially in communal areas of former homelands (Matsika et al., 2013). White et al. (1997) attribute this avoidance of electricity use to the costs of purchasing appliances, paying for electricity and long-term familiarity with using wood for cooking. Wessels et al. (2013) estimate the value of fuelwood from South African savannas to approx. 14.6 –77.4 million USD per year. This value represents savings in electricity and construction of new power stations by using fuelwood.

Understanding the complexity of socio-ecological systems in rural areas and how they may be influenced by climate change requires predictive modeling tools. Models can be used to explore a large option space of future land-use and climate change scenarios, and to identify sustainable land-use strategies that avoid degradation while ensuring a continuous provision of ecosystem services and associated economic values. Although a variety of modeling approaches has been developed and applied to develop sustainable management strategies for savanna rangelands (Boumans et al., 2002; De Groot et al., 2002; Higgins et al., 2007; Nelson et al., 2009; Tallis and Polasky, 2009), many of these models do not consider how climate change influences vegetation dynamics. Understanding future vegetation dynamics is essential to develop robust guidelines for future management policies. In this context, dynamic global vegetation models (DGVMs, Prentice et al., 2007) are appropriate tools to simulate vegetation dynamics. DGVMs are process-based vegetation models that integrate and simulate ecophysiological processes over a range of different ecosystem levels and allow to investigate biome patterns, ecosystem dynamics and biogeochemical fluxes over a wide range of temporal and spatial scales. DGVMs therefore allow to project future vegetation change and how it is influenced by land-use. Although DGVMs have been used in the context of land-use and management (for example Scheiter and Savadogo, 2016; Lindeskog et al., 2013; Kaplan et al., 2012; Olofsson and Hickler, 2008), they are typically not coupled with economic models and optimization algorithms that can serve to optimize management targets of multiple stakeholders.

In this study, we present a coupled economic-ecological model to investigate land-use strategies in savanna rangelands. We coupled the aDGVM (Scheiter and Higgins, 2009), a dynamic vegetation model for tropical and sub-tropical grass-tree ecosystems, with sub-models that simulate the impacts of livestock grazing by cattle and of fuelwood harvesting on savanna vegetation. Land-use sub-models were coupled with an economic model that evaluates costs and benefits of livestock owners and fuelwood collectors. Optimization algorithms were used to identify land-use strategies that maximize income for selected stakeholders until 2050 while accounting for the combined effects of climate and land-use change. We used the aDGVM because it is individual-based and allows to link impacts of herbivory (Scheiter and Higgins, 2012) and fuelwood harvesting to plant height, biomass or stem diameter. These processes cannot be simulated in models that ignore plant demography, such as simple differential equation models often used to describe vegetation dynamics in economic models (Higgins et al., 2007; Quaas et al., 2007). In addition, the aDGVM has been developed and parameterized particularly for African ecosystems and in Scheiter and Higgins (2009) we showed that it performs better in savanna ecosystems than alternative DGVMs.

We use this model framework to identify land-use strategies that maximize the benefit of livestock owners and fuelwood collectors until 2050 and compare these strategies to current land-use practice. As a case study, we parametrized the model for Bushbuckridge, a rural area in the Mpumalanga Province, South Africa. This study region exemplifies an area with a high density of rural communities that rely on natural resources from communal rangelands and a vegetation highly susceptible to climate change (Lehohla, 2012, 2015). We ask (Q1) how can stakeholders maximize their income during a planning horizon until 2050 while accounting for climate-change induced vegetation change? (Q2) How does a reduction in the fuelwood demand, for example due to increasing utilization of electricity as main energy source, influence the future vegetation state and vegetation recovery? (Q3) How does the management scenario that maximizes income in the planning horizon (identified in Q1) diverge from a realistic land-use scenario?

2. Materials and Methods

We couple three models, 1) the adaptive dynamic global vegetation model (aDGVM, blue boxes in Fig. 1, Scheiter and Higgins, 2009; Scheiter et al., 2012), 2) land-use routines that describe how grazing and fuelwood harvesting influence vegetation (purple box in Fig. 1), and 3) an economic model that defines the respective land-use policy of different stakeholders and the utility of land-use activities (orange boxes in Fig. 1). The model components are described in the following sections.

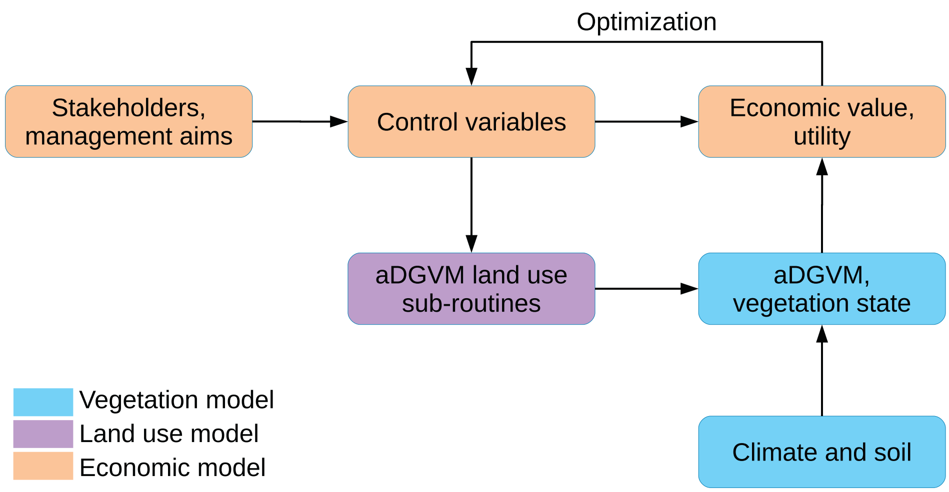

Fig. 1. Scheme of modeling framework. Blue boxes represent the vegetation model aDGVM (Section 2.1), the purple box represents the land-use component (Section 2.2), and orange boxes represent the economic model (Section 2.3).

2.1. Vegetation Model

To simulate vegetation dynamics, we used the aDGVM (adaptive dynamic global vegetation model, Scheiter and Higgins, 2009; Scheiter et al., 2012), a dynamic vegetation model developed with specific focus on tropical grass-tree systems. The aDGVM includes schemes to describe plant-physiological processes generally represented in DGVMs (Prentice et al., 2007) as well as model-specific processes that allow plant individuals to adjust leaf phenology and carbon allocation to environmental conditions. The aDGVM is individual-based, i.e., state variables such as photosynthetic rates, biomass, height, reproduction and mortality are simulated for individual plants rather than for cohorts or entire plant functional types. This approach allows us to take into account that herbivores (Scheiter and Higgins, 2012), fire (Scheiter and Higgins, 2009) and fuelwood harvesting (this study) are typically selective, i.e., the impact on vegetation is influenced by an individual's plant height, biomass or stem diameter. Thereby, different forms of biomass removal can have differential effects on plant population dynamics and ecosystem structure. Grasses are simulated as two super-individuals, either representing grasses beneath or between tree canopies. The aDGVM distinguishes four vegetation types: C_3 grasses, C_4 grasses, forest trees and savanna trees. These vegetation types differ in their photosynthetic pathway and shade and fire tolerance (for details see Scheiter et al., 2012). The aDGVM can simulate fire and fire management (see Scheiter et al., 2015, for a study looking at fire management impacts in Australian savannas). Yet, we ignore the fire component in this study as high grazing intensities in communal rangelands often imply low grass biomass, low fuel loads and therefore low fire activity. The aDGVM simulates vegetation for 1 ha stands with the site-specific environmental conditions. Depending on the specific model application, we assume that this 1 ha stand represents vegetation in a larger grid cell (upscaling); thereby, aDGVM can simulate vegetation from 1 ha resolution for local or site scale applications to coarser resolutions (e.g. 1° resolution) for regional or continental scale simulations.

The performance of the aDGVM was evaluated in previous studies. Scheiter and Higgins (2009) and Scheiter et al. (2012) show that the aDGVM can simulate the current distribution of vegetation in Africa better than alternative dynamic vegetation models. Scheiter and Higgins (2009) show that the aDGVM can reproduce biomass measurements obtained from a long-term fire manipulation experiment in the Kruger National Park (Experimental Burn Plots, Higgins et al., 2007). In Scheiter et al. (2018) we investigated the risk of biome shifts in the Limpopo Province, South Africa, induced by various climate change scenarios.

2.2. Land-use Models

We updated the aDGVM and included new sub-models to simulate grass biomass removal by grazing animals and tree biomass removal by fuelwood collectors (fuelwood harvesters). Both land-use forms are controlled by two parameters: (1) the visitation frequency that describes the number of visits of grazers or fuelwood collectors in an area per year, and (2) the amount of biomass removed per visit. These parameters can be controlled by the stakeholders (livestock owners and fuelwood collectors, see Section 2.3 for detailed description). In our approach, we simulate vegetation dynamics and land-use impacts for a representative 1 ha plot, hereafter denoted as 'target area'. Yet, it is assumed that the overall area available for grazing and fuelwood collection is larger than the target area and that grazing and fuelwood harvesting occur outside the target area on days without visitation. The size of the overall area influences land-use intensities and frequencies in the target area (see Section 2.3). Assuming that the utilization is homogeneous in the overall area, it is sufficient to simulate only the representative target area and it is ensured that the overall demands of grazers and fuelwood harvesters are met in any case.

2.2.1. Grazing

Days when grazing animals visit the target area are randomly generated and the visitation frequency f_{gr} describing the average number of visits per year is prescribed. If, on a given day in the simulation, a uniformly-distributed random number is less than f_{gr}, then animals visit the target area and remove D_{gr}^{day} (kg day^{-1}ha^{-1}) of the aboveground grass biomass. If the random number exceeds f_{gr}, animals meet their demand elsewhere in the overall area. Section 2.3.1 describes how f_{gr} and D_{gr}^{day} are defined. For simplicity, our approach assumes that days when the target area is visited by animals are random. Yet, in reality animals might visit the target area on subsequent days and then move to another area, which means that impacted areas may rest during longer periods and recover.

Grazing removes both dead and living aboveground grass biomass. The quantity of dead and living grass biomass removed by grazing is proportional to both pools' contribution to the total aboveground grass biomass. We simply assume that the nutritional value of living and dead grass biomass is equal. If the biomass demand of animals D_{gr}^{day} exceeds the available biomass in the target area, then dead and live aboveground biomass compartments of all grass individuals in the target area are set to a default minimum value (1 kg ha^{-1}) and a variable o_{gr} is increased by 1/365 in order to track the fraction of days per year on which demand exceeds supply. The variable o_{gr} is between zero and one, where zero indicates that grazing is supported by vegetation, while

values greater than zero indicate that demand exceeds supply.

2.2.2. Fuelwood Collection

We assume that the number of visits by fuelwood harvesters per year is defined by a frequency f_{fc}. If, on a simulated day, a uniformly distributed random number is less than f_{fc}, then the target area is visited and an amount D_{fc}^{day} (kg day^{-1}ha^{-1}) of woody biomass is removed. If the random number exceeds f_{fc}, fuelwood is harvested elsewhere in the overall area. The parameters f_{fc} and D_{fc}^{day} are variable and defined by the stakeholders. Section 2.3.2 describes how these parameters are calculated.

If the demand D_{fc}^{day} is less than 35% of the dead woody biomass at the simulated vegetation stand, then all fuelwood is removed from dead biomass. The 35% threshold implies that only this proportion of dead wood biomass is appropriate as fuel or that fuelwood collectors do not utilize the entire target area for wood collection. If the demand D_{fc}^{day} exceeds 35% of the dead woody biomass, fuel biomass is collected from both dead and living aboveground woody biomass. The amounts removed from dead and living biomass are defined by the proportions of living and dead woody biomass in the target area. We use a parameter δ, to track if biomass is removed from dead woody biomass only ($\delta = 0$) or both from dead and living biomass ($\delta = 1$).

As the aDGVM is individual-based, we assign a probability of being selected for wood harvesting, $R(d)$, to each tree. This probability is a function of tree stem diameter. Following Twine and Holdo (2016), we assume that the utilization probability $R(d)$ is zero if the stem diameter d is less than 1 cm or greater than 20 cm, and one when the stem diameter is between 4 cm and 10 cm. For trees with diameters between 1 and 4 cm or between 10 and 20 cm, we use linear functions between zero and one to describe the utilization probability (Fig. 2). If a uniformly-distributed random number is less than the tree's utilization probability, the tree is chosen for fuelwood collection and 90% of the woody aboveground biomass of that tree is removed. Hence, we assume that the entire tree is harvested except for the stump and roots. Potential trees for fuelwood harvesting are selected randomly. This selection procedure is repeated until the biomass demand D_{fc}^{day} has been removed from the tree population, or until all trees in the population have been selected and impacted by fuelwood removal. In aDGVM, damaged trees can re-sprout from their root reserves and regrow. Hence, fuelwood harvesting does not directly kill vegetation but possibly indirectly via a negative carbon balance during the recovery phase. The utilization probability $R(d)$ is only used for living trees, for dead tree biomass aDGVM does not separate between individuals but only simulates one dead biomass compartment.

If fuelwood demand on a given day exceeds biomass supply in the target area, then the fraction of days per year during which overharvesting occurs, o_{fc}, is increased by 1/365. The variable o_{fc} is between zero and one, where zero indicates that fuelwood collection is supported by vegetation, while values greater than zero indicate that the demand exceeds the supply of trees appropriate for fuelwood harvesting.

Fig. 2. Utilization probability of trees for fuelwood harvesting as a function of tree stem diameter, $R(d)$.

2.3. Economic Model

We couple the aDGVM with a semi-empirical economic model that describes the value of different ecosystem services and land-use activities to different stakeholders. Here, we assume that stakeholders are individual farmers or households. Our approach assumes that ecosystem services are used for subsistence and it does not explicitly account for stakeholders trading with their products. A land-use strategy is defined by a set of control parameters that can be adjusted by stakeholders. We consider three different types of stakeholders, namely livestock owners (hereafter LO), fuelwood collectors (hereafter FC), as well as livestock owners and fuelwood collectors combined (hereafter CB). In the model, we calculate economic variables on an annual time step, with t denoting years. Simulations are split into a historic period $t_{-m},\ldots,t_0$ and a planning horizon $t_1,\ldots,t_n$. Management is initialized at the start of the historic period in year t_{-m} to ensure that the model is in a steady state at the onset of the planning horizon t_1. See also Section 2.5 for details of the model set-up.

2.3.1. Livestock Owner (LO)

Livestock owners can control the number of animals $T(t)$ in year t on a given area A_{gr} available for grazing. The animal number $T(t)$ is adjusted by the optimization algorithm such that the utility function is maximized. We assume an average and constant biomass consumption of D_{lu} per livestock unit (LU) and per day (see Table 1). The biomass required by all animals per year is then given as $D_{gr}(t) = 365 \cdot T(t)D_{lu}$ and the daily biomass requirement is given as $D_{gr}^{day}(t) = T(t)D_{lu}$. The daily requirement D_{gr}^{day} is equal to the biomass that has to be removed from the target vegetation stand per visit. In the model we assume that the number of animals, and hence biomass demand by animals, is constant during the historic period, while it can be adjusted by the livestock owner on a yearly basis during the planning horizon $t_1,\ldots,t_n$. In case the animal numbers are adjusted, the number of animals changes by I_{gr}% per year, where I_{gr} is a control parameter that is selected by LO, optimized by the optimization algorithm, and constant over the planning horizon. We do not simulate dynamics of the animal population, for example by buying, selling or slaughtering animals, explicitly. We also ignore age structure and gender-specific differences of the animals, assuming an average nutritional requirement per individual.

The visitation frequency of livestock in the target area is influenced by the total area available for grazing A_{gr},

$$f_{gr} = \frac{1}{A_{gr}}. \tag{1}$$

In our simulations, A_{gr} and hence f_{gr} are constant during both the historic period and the planning horizon. As stated in Section 2.2, we assume that the total area A_{gr} available for livestock is larger than the simulated representative 1 ha target area and that animals meet their demand elsewhere on A_{gr} on days when they do not visit the simulated target area.

The number of animals influences both costs and benefits for the livestock owner. Benefits from livestock in year t include values of milk (G_{milk}), meat (G_{meat}), dung used as fertilizer (G_{fert}), for heating (G_{heat}) or as construction material (G_{cons}), leather (G_{leath}), transport (G_{trans}), labor (G_{labor}) and cultural purposes (G_{cult}). The total gain from grazing per year is given as

$$\begin{aligned} G_{gr}(t) = {} & [G_{milk}(t) + G_{meat}(t) + G_{fert}(t) + G_{heat}(t) + G_{cons}(t) \\ & + G_{leath}(t) + G_{trans}(t) + G_{labor}(t) + G_{cult}(t)]\cdot r_{ogr}. \end{aligned} \tag{2}$$

Here, r_{ogr} describes how gain $G_{gr}(t)$ is reduced if animal demand exceeds biomass supply in the grass layer. We use the fraction of days per year

Table 1
Parameters in the sub-model for grazing and the livestock owner (LO). In column 'Value', numbers indicate that the parameter is constant, 'Control' indicates parameters that define the land-use strategy and that are modified by the optimization algorithm, and 'Variable' indicates parameters that are calculated from constants and control parameters.

Name	Description	Value	Unit	Ref
A_{gr}	Area available for grazing	5	ha	3
f_{gr}	Grazing visitation frequency on target area	Variable	year^{-1}	
C_{gr}	Set of control parameters of livestock owner	Control	–	
D_{lu}	Daily demand of a single livestock unit	45	kg	3
$D_{gr}(t)$	Annual demand of all animals in year t	Variable	kg	
D_{gr}^{day}	Demand of animals per visit	Variable	kg day^{-1} ha^{-1}	
$G_{gr}(t)$	Gain from livestock in year t	Variable	ZAR	
I_{gr}	Change in animal number after 2016	Control	% year^{-1}	
$L_{gr}(t)$	Losses from livestock in year t	Variable	ZAR	
$L_{gr}^{fix}(t)$	Fixed costs of livestock owner	344.20	ZAR	3
$L_{gr}^{loss}(t)$	Loss of value of livestock unit	Variable	ZAR	
λ_{lu}	Average life span of livestock unit	15	years	3
$M(t)$	Milk production in year t	Variable	liters	
M_p	Milk production per livestock unit and year	600	liters	2
$o_{gr}(t)$	Fraction of days per year where demand exceeds supply	Variable	year^{-1}	
P_{meat}	Fraction of animals for meat production	Control	fraction	
P_{milk}	Fraction of animals for milk production	Control	fraction	
P_{fert}	Fraction of dung used as fertilizer	Control	fraction	
P_{heat}	Fraction of dung used for heating	Control	fraction	
P_{cons}	Fraction of dung used for construction	Control	fraction	
r_{ogr}	Utility reduction if demand exceeds supply	Variable	no units	
S_{lu}	Dung produced by a livestock unit per year	2000	liters	3
$S(t)$	Dung produced by all animals in year t	Variable	kg	
$T(t)$	Number of animals at time t	Control	animals	
τ	Discount rate of livestock owner	Variable	year^{-1}	
$U_{gr}(t)$	Utility from livestock in year t	Variable	ZAR	
$\mathbf{U}_{gr}$	Mean utility from livestock in planning horizon	Variable	ZAR	
V_{lu}	Market value of a livestock unit	8443.00	ZAR	1

References: 1 = oral communication (W. Twine); 2 = Goldschmidt (1981); 3 = plausible values estimated by authors

where demand exceeds supply, $o_{gr}(t)$ as defined in Section 2.2.1 to describe the reduction of income,

$$r_{ogr} = 1 - \frac{o_{gr}^4}{1 + o_{gr}^4}. \tag{3}$$

We assume that the relation between overgrazing and income is sigmoidal and non-linear with no effect if overgrazing occurs only rarely and strong effect if overgrazing occurs frequently. Based on this equation, income from grazing $G_{gr}(t)$ is reduced by 50% should overgrazing occur on each day of the year. This can only happen if the total area available for animals, A_{gr}, equals 1 ha, the size of the simulated target area. The exponent in Eq. (3) was derived from trial simulations because empirical data to parametrize the equation were not available. Reduced income by using r_{ogr} implicitly accounts for additional fodder that livestock owners buy in case grass biomass is not sufficient or that productivity of animals is reduced due to underfeeding. These aspects are not represented explicitly in our model.

The incomes from different components of $G_{gr}(t)$ are calculated with diminishing marginal utility functions. This implies that at low animal numbers, utility increases rapidly when animal numbers are increased, but at higher animal numbers, the utility increase levels off when additional animals are added. This approach reflects that high utilization of a service (i.e. cattle grazing) by people in a community also implies

Table 2
Parameters in the sub-model for livestock owners (LO). In column 'Value', numbers indicate that the parameter is constant, 'Control' indicates parameters that define the land-use strategy and that are modified by the optimization algorithm, and 'Variable' indicates parameters that are calculated from constants and control parameters.

Name	Description	Value	Unit	Ref
G_{milk}	Income from milk production	Variable	ZAR	
G_{meat}	Income from meat production	Variable	ZAR	
G_{fert}	Income from dung used as fertilizer	Variable	ZAR	
G_{heat}	Income from dung used for heating	Variable	ZAR	
G_{cons}	Income from dung used for construction	Variable	ZAR	
G_{leath}	Income from leather production	Variable	ZAR	
G_{trans}	Income from cattle used for transport	Variable	ZAR	
G_{labor}	Income from cattle used for labor	Variable	ZAR	
G_{cult}	Income from cattle used for cultural purposes	Variable	ZAR	
G_{milk}^{max}	Maximum income from milk production	2104.68	ZAR	1
G_{meat}^{max}	Maximum income from meat production	867.27	ZAR	1
G_{fert}^{max}	Maximum income from dung used as fertilizer	838.47	ZAR	1
G_{heat}^{max}	Maximum income from dung used for heating	407.81	ZAR	1
G_{cons}^{max}	Maximum income from dung used for construction	88.72	ZAR	1
G_{leath}^{max}	Maximum income from leather production	20.06	ZAR	1
G_{trans}^{max}	Maximum income from cattle used for transport	654.90	ZAR	1
G_{labor}^{max}	Maximum income from cattle used for labor	313.75	ZAR	1
G_{cult}^{max}	Maximum income from cattle used for cultural purposed	8443.00	ZAR	2
r_{milk}	Fraction using cattle for milk production	0.42	fraction	1
r_{meat}	Fraction using cattle for meat production	0.83	fraction	1
r_{fert}	Fraction using dung as fertilizer	0.91	fraction	1
r_{heat}	Fraction using dung for heating	0.18	fraction	1
r_{cons}	Fraction using dung for construction	0.56	fraction	1
r_{leath}	Fraction using cattle for leather production	0.49	fraction	1
r_{trans}	Fraction using cattle for transport	0.15	fraction	1
r_{labor}	Fraction using cattle for labor	0.50	fraction	1
r_{cult}	Fraction using cattle for cultural purposes	0.08	fraction	2

References: 1 = Shackleton et al. (2005); 2 = plausible value estimated by authors

high demand and higher value of the service to stakeholders. We used this approach because we do not explicitly simulate the market where costs and benefits are regulated by supply and demand and trading of animals.

The utility of livestock for labor or transport is described by the maximum values that can be obtained from labor or transport (G_{labor}^{max}, G_{trans}^{max} per year, Table 2), the average fraction of livestock owners using animals for labor or transport (r_{labor}, r_{trans}, Table 2), and the number of animals,

$$G_{labor}(t) = G_{labor}^{max}\ r_{labor}\ e^{-\frac{1}{T(t)}} \tag{4}$$

$$G_{trans}(t) = G_{trans}^{max}\ r_{trans}\ e^{-\frac{1}{T(t)}} \tag{5}$$

We assume that utility from milk is linked to milk production $M(t)$ of all animals per year such that

$$G_{milk}(t) = G_{milk}^{max}\ r_{milk}\ e^{-\frac{1}{M(t)}} \quad \text{where} \quad M(t) = M_p\ P_{milk}\ T(t). \tag{6}$$

Here, M_p is the milk produced per animal per year and P_{milk} is a control parameter describing the proportion of animals that produce milk. The maximum income from milk production per year is given by G_{milk}^{max}, and r_{milk} is the proportion of livestock owners that keep animals for milk production.

Dung can be used as fertilizer, for heating or as construction material. The proportions used as fertilizer (P_{fert}) and for heating (P_{heat}) are control parameters adjusted by the livestock owner and modified during the optimization, the proportion of dung used for construction is calculated as $P_{cons} = 1 - P_{fert} - P_{heat}$. The utility of dung is calculated as

$$G_{fert}(t) = G_{fert}^{max}\ r_{fert}\ e^{-\frac{1}{S(t)P_{fert}}} \tag{7}$$

$$G_{heat}(t) = G_{heat}^{max}\ r_{heat}\ e^{-\frac{1}{S(t)P_{heat}}} \tag{8}$$

$$G_{cons}(t) = G_{cons}^{max}\ r_{cons}\ e^{-\frac{1}{S(t)P_{cons}}} \tag{9}$$

Here, G_{fert}^{max}, G_{heat}^{max} and G_{cons}^{max} are maximum incomes from alternative utilization of dung, r_{fert}, r_{heat} and r_{cons} are the average fractions of livestock owners using dung for fertilizing, heating and construction. The dung produced by all animals in year t is calculated as

$$S(t) = S_{lu}\ T(t), \tag{10}$$

where S_{lu} is the dung produced per animal per year.

The utility of meat and leather production is calculated using the maximum utility of meat and leather production (G_{meat}^{max}, G_{leath}^{max}), the average fractions of lifestock owners using animals for meat and leather production (r_{meat}, r_{leath}) and the fraction of animals slaughtered for meat production per year, P_{meat}:

$$G_{meat}(t) = G_{meat}^{max}\ r_{meat}\ P_{meat}\ e^{-\frac{1}{T(t)}} \tag{11}$$

$$G_{leath}(t) = G_{leath}^{max}\ r_{leath}\ P_{meat}\ e^{-\frac{1}{T(t)}}. \tag{12}$$

We assume that slaughtered animals are always used for both meat and leather production. In the model, livestock can be used for cultural purposes, for instance as presents for weddings, seed money for children or for ceremonies. The utility is calculated as

$$G_{cult}(t) = G_{cult}^{max}\ r_{cult}\ e^{-\frac{1}{T(t)}}, \tag{13}$$

where G_{cult}^{max} is the maximum utility and r_{cult} is the fraction of livestock owners using animals for cultural purposes.

Income is reduced by fixed costs $L_{gr}^{fix}(t)$, for example for maintaining fences or collecting manure, and by loss of value due to aging and mortality of animals $L_{gr}^{loss}(t)$. The total loss per year is $L_{gr}(t) = L_{gr}^{fix}(t) + L_{gr}^{loss}(t)$. Fixed costs $L_{gr}^{fix}(t)$ are assumed to be constant for a livestock owner and not related to animal numbers. The loss of value is calculated as $L_{gr}^{loss}(t) = \tau T(t)$, where τ is the discount rate,

$$\tau = \frac{V_{lu}}{\lambda_{lu}}. \tag{14}$$

Here, V_{lu} is the cost of buying an animal and λ_{lu} is the expected life time of an animal (see Table 1 for parameter values). In Eq. (14) we assume that all animals are used only for subsistence while we do not explicitly simulate trading with products such as meat, leather or other products.

The utility in year t is given as the difference between gain and loss in year t,

$$U_{gr}(t) = G_{gr}(t) - L_{gr}(t), \tag{15}$$

and the average annual utility in the planning horizon $t_1,\ldots,t_n$ is

$$\mathbf{U}_{gr} = \frac{1}{n}\sum_{t=t_1}^{t_n} U_{gr}(t). \tag{16}$$

2.3.2. Fuelwood Collector (FC)

Fuelwood collectors can control the annual fuelwood demand, $D_{fc}(t)$, and the visitation frequency (i.e. the average number of visitations per year), $f_{fc}(t)$, see Section 2.2.2. Both the annual demand D_{fc} and the visitation frequency f_{fc} are adjusted by the optimization algorithm such that utility is maximized. From the annual demand we calculate the daily demand as D_{fc}^{day}. We assume that the fuelwood collected per year can be adjusted by the stakeholder and that it can increase or decrease by I_{fc}% per year during the planning horizon $t_1,\ldots,t_n$. The control parameter I_{fc} is adjusted by the optimization routines.

The utility of fuelwood collection is calculated by the maximum utility of fuelwood G_{fc}^{max} and by a rate that describes how the utility changes with increasing demand,

$$G_{fc}(t) = G_{fc}^{max}\ e^{-\frac{1}{0.0008D_{fc}(t)}} \tag{17}$$

The parameter in Eq. (17) was derived from trial simulations because empirical data to parametrize the equation were not available. Fixed costs $L_{fc}^{fix}(t)$ are related to the effort required for wood collection but we assume that fixed costs are not linked to the amount of biomass removed, D_{fc}^{day}. This assumption is justified as long as the amount of fuelwood collected per visit is low. Fixed costs for collecting dead wood lying on the ground are lower than fixed costs for collecting live biomass, because this requires more time and additional tools such as ladders or saws. The additional cost is given by L_{fc}^{live} and by a factor δ that defines if biomass is removed from dead biomass only or if biomass is removed both from dead and live biomass (see Section 2.2.2).

Fuelwood collection also implies variable costs $L_{fc}^{var}(t)$. These costs correspond to opportunity costs and are included because fuelwood collection is time-consuming. This approach considers time as monetary value that is used to represent the incentives of the stakeholder. We calculate variable costs as

$$L_{fc}^{var}(t) = 0.1D_{fc}(t)\ e^{0.0003\ D_{fc}(t)}. \tag{18}$$

The parameters in Eq. (18) were derived from trial simulations. We assume that fuelwood is collected as long as the costs for collecting wood are lower than the costs for buying wood, $V_{buy} = V_{fc}\ D_{fc}(t)$, where V_{fc} is the market value of fuelwood.

We assume that the benefit of fuelwood collecting decreases when demand exceeds supply and describe this relation using the sigmoidal function

$$r_{ofc} = 1 - \frac{o_{fc}^4}{1 + o_{fc}^4}, \tag{19}$$

where o_{fc} is the fraction of days per year during which demand exceeds supply (see Section 2.2.2).

The utility in year t is given as the difference between gain and loss in year t,

$$U_{fc}(t) = G_{fc}(t)\ r_{ofc} - L_{fc}^{fix}(t) - \delta L_{fc}^{live}(t) - L_{fc}^{var}(t), \tag{20}$$

and the average annual utility in the planning horizon $t_1,\ldots,t_n$ is

$$\mathbf{U}_{fc} = \frac{1}{n}\sum_{t=t_1}^{t_n} U_{fc}(t). \tag{21}$$

2.3.3. Livestock Owner and Fuelwood Collector Combined (CB)

For the combined stakeholder, the utility function is simply defined by the sum

$$\mathbf{U}_{cb} = \mathbf{U}_{gr} + \mathbf{U}_{fc} \tag{22}$$

of the utility functions of the livestock owner and the fuelwood harvester.

2.4. Management Aims and Scenarios

2.4.1. Maximize Income (MAX)

The management aim of stakeholders in the MAX scenario is to maximize the utility function during the planning horizon $t_1,\ldots,t_n$. We therefore run the genetic optimization algorithm DEoptim (Mullen et al., 2011) to maximize the utility function of the livestock owner LO (Eq. (16)), the fuelwood collector FC (Eq. (21)), and the combined livestock owner and fuelwood collector CB (Eq. (22)),

$$\max_{C_{gr}} \mathbf{U}_{gr} \quad \text{or} \quad \max_{C_{fc}} \mathbf{U}_{fc} \quad \text{or} \quad \max_{C_{cb}} \mathbf{U}_{cb}. \tag{23}$$

Here, $C_{gr} = (T(t_1), I_{gr}, P_{meat}, P_{milk}, P_{fert}, P_{heat}, P_{cons})$ is the set of control parameters of the stakeholder LO, $C_{fc} = (f_{fc}, D_{fc}(t_1), I_{fc})$ is the set of control parameters of the stakeholder FC and $C_{cb} = (T(t_1), I_{gr}, P_{meat}, P_{milk}, P_{fert}, P_{heat}, P_{cons}, f_{fc}, D_{fc}(t_1), I_{fc})$ is the set of control

Table 3
Parameters used in the sub-models for the fuelwood collector (FC) and the combined livestock owner and fuelwood collector (CB). In column 'Value', numbers indicate that the parameter is constant, 'Control' indicates parameters that define the land-use strategy and that are modified by the optimization algorithm, and 'Variable' indicates parameters that are calculated from constants and control parameters.

Name	Description	Value	Unit	Ref
f_{fc}	Fuelwood collection frequency on simulated stand	Control	year^{-1}	
C_{fc}	Set of control parameters for fuelwood collection	Control	–	
$D_{fc}(t)$	Annual demand of fuelwood	Control	kg	
D_{fc}^{day}	Demand per visit	Variable	kg	
δ	Variable counting if fuelwood taken from dead biomass	Variable	No units	
d	Stem diameter of tree	Variable	cm	
$G_{fc}(t)$	Gain from fuelwood harvesting in year t	Variable	ZAR	
G_{fc}^{max}	Maximum gain from fuelwood harvesting	1500	ZAR	1
I_{fc}	Change in fuelwood demand after 2016	Control	% year^{-1}	
L_{fc}^{fix}	Fixed costs of fuelwood collection	30	ZAR	2
L_{fc}^{live}	Additional fixed costs of collecting live biomass	10	ZAR	2
L_{fc}^{var}	Variable costs of fuelwood collection	Variable	ZAR	
o_{fc}	Fraction of days per year where demand exceeds supply	Variable	year^{-1}	
r_{ofc}	Utility reduction if demand exceeds supply	Variable	No units	
$R(d)$	Tree utilization probability for fuelwood	Variable	fraction	
V_{fc}	Market value of fuelwood	0.426	ZAR	1
V_{buy}	Cost of buying fuelwood	Variable	ZAR	
$U_{fc}(t)$	Utility from fuelwood in year t	Variable	ZAR	
$\mathbf{U}_{fc}$	Mean utility from fuelwood in planning horizon	Variable	ZAR	
C_{cb}	Set of control parameters for livestock owner and fuelwood combined	Control	–	
$\mathbf{U}_{cb}$	Mean utility from livestock owner and fuelwood harvester combined in planning horizon	Variable	ZAR	
t	Year	Variable	year	
t_1	First year of planning horizon	2016	year	
t_n	Last year of planning horizon	2050	year	
n	Length of planning horizon	Variable	years	
t_{-m}	First year with landuse impacts	1960	year	

References: 1 = Matsika et al. (2013); 2 = plausible value estimated by authors

parameters of the stakeholder CB. The control parameters are constrained by minimum and maximum values in the optimization (Table 4). The ranges of the values were selected such that they include realistic values and such that the optimization does not converge towards the minimum or maximum of the ranges. Exceptions are P_{milk} and f_{fc} because they can only be between zero and one, and P_{fert}, P_{heat} and P_{cons}, because these three values have to sum to one. In the MAX scenario, we assume that cattle number $T(t)$ and fuelwood demand $D_{fc}(t)$ are not selected and pre-defined by the stakeholders but that they are derived by the optimization routine such that the utility functions are maximized.

In the MAX scenario, the behavior of stakeholders is fully rational. Stakeholders make decisions on land-use based on long-term economic utility until 2050 even if this implies lower stocking and fuelwood harvesting rates. This strategy does not typically reflect reality where land-use decisions are made for shorter planning horizons and in a more opportunistic way. Yet, this case can serve as a baseline for comparisons between alternative scenarios.

2.4.2. Change in Energy Mix (EMX)

In the EMX scenario, we assume that the energy mix of households changes towards a higher proportion of electricity and associated reductions in fuelwood demand and fuelwood harvesting. We therefore run the model with the optimal management strategies from the MAX scenario for FC and CB until 2016 and reduce fuelwood collection by a constant rate of I_{fc}% per year during the planning horizon until 2050. We calculated I_{fc} such that the annual wood demand D_{fc} in 2050 is 5% of the wood demand in 2016, i.e. I_{fc} = 13.4%. This represents a situation where the main energy source of stakeholders is electricity, but fuelwood is still used in small quantities. We track how this reduction influences the vegetation state during the planning horizon. Note that we do not consider economic aspects of changes in the energy mix; this would require consideration of payments for electric devices or payments for alternative energy sources.

2.4.3. Realistic Grazing and Fuelwood Harvesting Intensity (REI)

The MAX scenarios identify intensities and visitation frequencies of grazing and fuelwood harvesting that maximize the utility functions. Yet, in reality, the intensities are prescribed by the actual fuelwood demand and animal numbers of households. We therefore simulated vegetation dynamics with prescribed and realistic values for animal numbers and fuelwood demand and then calculated the values of the utility functions. The values of the control parameters used in the REI scenario are provided in Table 4. The selected value of 3.5 t/year for fuelwood harvesting is within the range of observations by Matsika et al. (2013), the cattle density of 0.88 animals/ha was obtained from Parsons et al. (1997).

2.5. Simulation Experiments

We conducted all simulations for the Athol village in the Bushbuckridge Municipality, Mpumalanga, South Africa (24.72° S,

Table 4
Ranges of control variables of land-use strategies used for the optimization, and utility and control variables obtained from the model optimization in different scenarios. See Tables 1 and 3 for variable names. Control variables for all REI scenarios were pre-defined to represent a realistic scenario.

Name	Min.	Max.	LO MAX	FC MAX	CB MAX	LO REI	FC REI	CB REI
T	0.01	20	0.076	-	0.068	0.88	-	0.88
I_{gr}	−10	10	0.056	-	0.164	0	-	0
P_{meat}	0	0.77	0.77	-	0.76	0.76	-	0.76
P_{milk}	0	1	1	-	1	1	-	1
P_{fert}	0	0.5	0.5	-	0.5	0.5	-	0.5
P_{heat}	0	0.5	0.27	-	0.35	0.27	-	0.27
P_{cons} [1]	0	1	0.23	-	0.15	0.23	-	0.23
f_{fc}	0.01	1	-	1	0.99	-	1	1
D_{fc}	10	10,000	-	1337	1356	-	3500	3500
I_{fc}	−10	10	-	0.12	−0.18	-	0	0
$\mathbf{U}_{gr}$			1351		1350	926		
$\mathbf{U}_{fc}$				69	67		−344	
$\mathbf{U}_{cb}$					1417			558

[1]Calculated as $1 - P_{fert} - P_{heat}$.

31.35° E, Matsika et al., 2013) because long-term socio-ecological research in this municipality provides a sound data basis (e.g. Matsika et al., 2013; Twine and Holdo, 2016). Bushbuckridge is a densely populated rural area with high unemployment rate, low economic development and income. Subsistence farming strongly contributes to livelihoods, although it is not the mainstay. Social grants and income from migrant family members are a major contribution. Communal land is used for livestock, non-timber forest products and cultivation.

To run aDGVM, we first conducted a model spin-up of 200 years using the repeated monthly climatology averaged for the period between 1961 and 1990 (New et al., 2002). Daily precipitation was created from the monthly climatology by using mean monthly precipitation, coefficient of variation and number of rainfall events per month, following New et al. (2002). During the spin-up phase, model variables stabilize and reach a steady state. After the 200-year spin-up, we increased atmospheric CO_2 concentrations and scaled monthly temperature and precipitation with historic and future anomalies from the IPCC RCP 8.5 scenario to simulate the period between 1960 and 2050. Anomalies were estimated from climate projections simulated by MPI-ESM-LR, the Earth system model (ESM) developed by the Max Planck Institute (MPI) for Meteorology Hamburg (Giorgetta et al., 2013). As stated in Section 2.1, we ignored fire in all simulations although aDGVM has a fire sub-model (Scheiter and Higgins, 2009).

As a baseline scenario, we simulated vegetation without grazing and fuelwood collection between 1960 and 2050. This scenario represents 'natural' vegetation dynamics in the absence of any land-use activity, based on climate change alone. We then conducted different simulation experiments to investigate the key questions (see Section 1). To study how stakeholders can maximize their utility until 2050 (question Q1 in Section 1), we maximized the utility functions for livestock owners LO, fuelwood harvester FC, and the combination CB (Eq. (23)). Then, we applied the scenario with changing energy mix (EMX) throughout the planning horizon between 2016 and 2050 to test the impact on the utility and vegetation state. We compared the tree stem diameter distribution in the MAX scenario and the EMX scenario in 2050 to study vegetation recovery after a change in the energy mix (question Q2 in Section 1). Finally, we conducted simulations with fixed grazing and fuelwood harvesting intensities (REI scenario) to compare the utility function between the MAX scenario where income is maximized and the REI scenario where harvesting and livestock intensities are realistic, i.e., based on the current demand of stakeholders (question Q3 in Section 1).

In all scenarios, we introduced management in 1960, i.e. after completion of the spin-up phase and at the beginning of the transient simulations. We kept all control parameters (C_{gr},C_{fc},C_{cb}) constant until 2016. In the planning horizon between 2016 and 2050, control parameters I_{gr} and I_{fc} were used to increase or decrease grazing and wood cutting intensity, respectively.

3. Results

3.1. Vegetation Dynamics in the Absence of Land-use

In the baseline scenario, grass biomass remains approximately constant in the period between 1960 and 2050 (Fig. 3a) while tree biomass increases from approximately 20 t /ha in 1960 to 26 t /ha in 2016 and 32 t /ha in 2050 (Fig. 3b). This tree biomass increase can be explained by elevated CO_2 concentrations; elevated CO_2 acts as a fertilizer in aDGVM and increases woody plant growth (Higgins and Scheiter, 2012; Scheiter and Higgins, 2009), while grasses simulated at the study site are predominantly of C_4-type and therefore do not benefit from CO_2 fertilization.

3.2. Optimizing Utility – The MAX Scenario

Grazing and fuelwood collection influence grass and tree biomass. When only grazing is applied and utility is maximized (LO MAX scenario), grass biomass and tree biomass are similar to the baseline scenario after the introduction in 1960 (Fig. 3a, b). The optimal grazing intensity is only moderate (0.076 animals per ha, Table 4) because overgrazing reduces income and is therefore avoided by stakeholders. Animal numbers and the grazing yield, i.e. the amount of grass biomass removed by animals, are stable during the planning horizon (Fig. 4a). Hence, the utility is almost constant, averaging ZAR 1351 per livestock owner per year (Fig. 4b, Table 4).

When fuelwood collection is introduced after 1960 in the FC MAX scenario, tree biomass drops to approximately 14 t /ha in 1975 and gradually recovers to approximately 20 t /ha in 2016 (Fig. 3b). During the planning horizon, woody biomass increases to approximately 24 t /ha in 2050. Tree biomass reduction implies reduced resource competition for grasses and therefore more grass biomass than in the control scenario (Fig. 3a). Both harvesting yield (Fig. 4c) and the utility (Fig. 4d) are relatively stable during the planning horizon. However, environmental variability implies variability in tree productivity and fuelwood demand may exceed productivity and fuelwood supply in some years. This causes variability in the harvested biomass as well as negative values of the utility in these years (Fig. 4d). Negative utility means that the fuelwood demand exceeds the supply and that the costs for collecting wood exceed the costs for buying wood. The average utility during the planning horizon is ZAR 69 per fuelwood collector per year (Table 4).

When both grazing and fuelwood collection are applied in the CB MAX scenario, tree biomass in the planning horizon is lower than in the baseline scenario and the FC MAX scenario with only fuelwood collection (Fig. 3b). At the end of the planning horizon in 2050, tree biomass is 18 t /ha. Grazing and fuelwood harvesting yield (Fig. 4e) and utility (Fig. 4f) are stable during the planning horizon. The average utility in the planning horizon is ZAR 1417 per day (ZAR 1350 from livestock, ZAR 67 from fuelwood harvesting, Table 4), a value almost identical to the sum of the utilities in the LO and FC scenarios (ZAR 1420).

3.3. Characteristics of Optimal Land-use Strategies

Our approach allows us to investigate the control variables defining an optimal management scenario with respect to the utility functions as well as the associated yields and ecosystem state in more detail (Table 4). Here we only provide results for the stakeholder CB. Fuelwood harvesting yield in the CB MAX scenario is at the high end of the range of all scenarios generated during the optimization process (1356 kg /year, within a range between 0 and ca. 1500 kg /year generated during model optimization, Fig. 5a). Optimal grazing yield is found at an intermediate value (974 kg /year, from within a range between 0 and ca. 4000 kg /year generated during model optimization). Accordingly, at the end of the planning horizon in 2050, the wood biomass in this scenario adopts a low value within the range of all alternative management scenarios generated during model optimization (ca. 22 t /ha within a range between 20 and 36 t /ha, Fig. 5b), while grass biomass is at an intermediate value (ca. 5 t /ha within a range between 1 and 6 t /ha).

The optimization process provides information regarding the sensitivity of the utility function to changes in the control parameters, i.e. to which degree small changes in control parameters influence the utility. The utility is sensitive to the number of animals (T, Fig. 6a). Modest increases of animal numbers imply overgrazing and a reduction

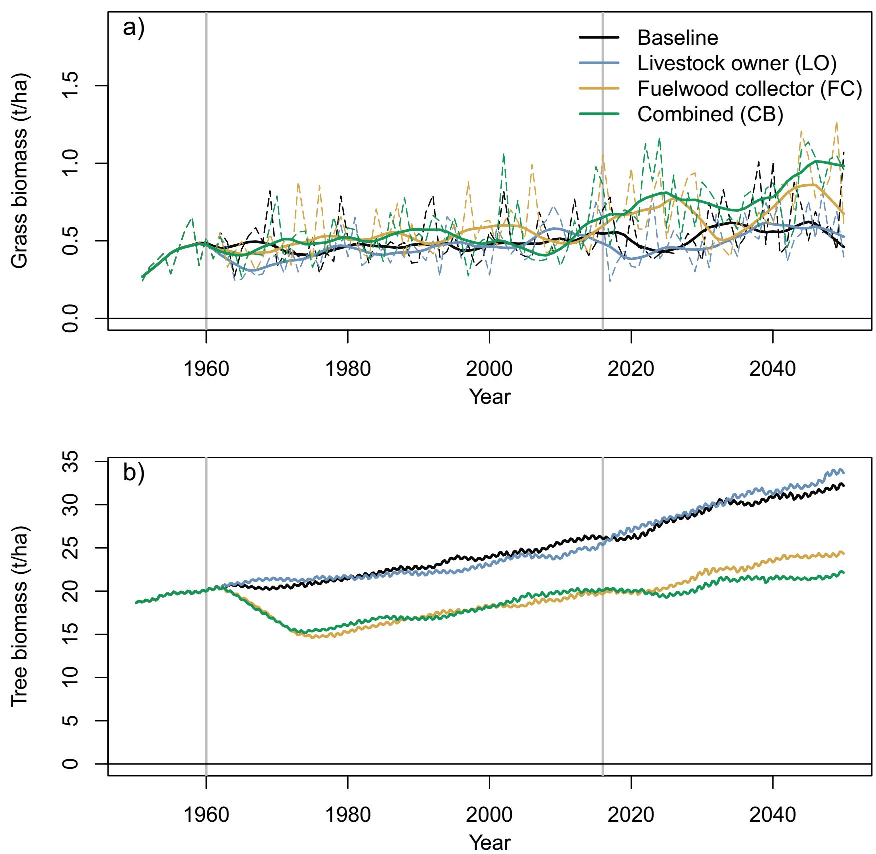

Fig. 3. Impacts of grazing, fuelwood harvesting and combined grazing and fuelwood harvesting on grass (a) and tree (b) biomass. The panels show the optimal solutions in the MAX scenario, that is the solutions where utility is maximized. For grass biomass, dashed lines represent annual maximum grass biomass values, bold lines represent smoothened time series (locally-weighted polynomial regression). The gray lines indicate the introduction of management in 1960 and the start of the planning horizon in 2016.

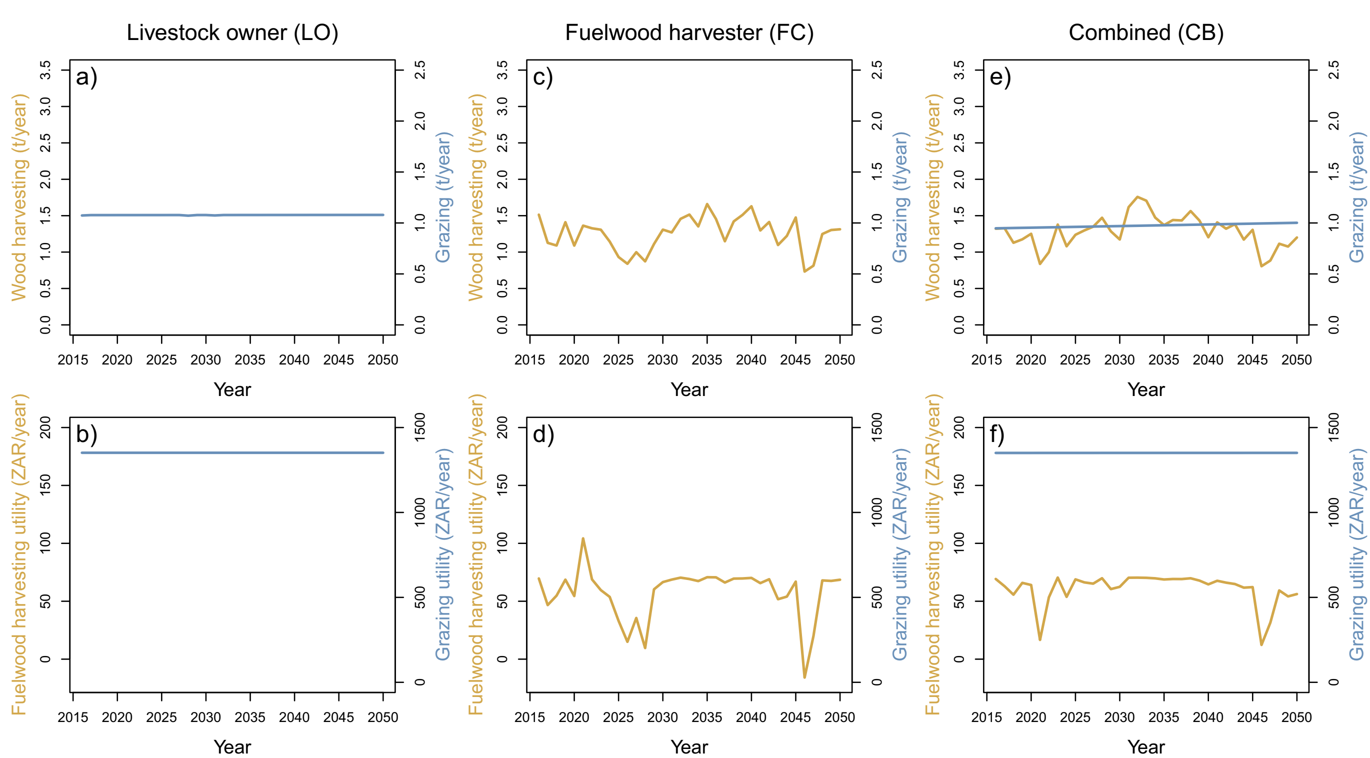

Fig. 4. Impacts of grazing (a, b), fuelwood harvesting (c, d) and combined grazing and fuelwood harvesting (e, f) on yield (a, c, e) and utility (b, d, f) in the MAX scenario. Note that the axis scaling differs for fuelwood harvesting and grazing.

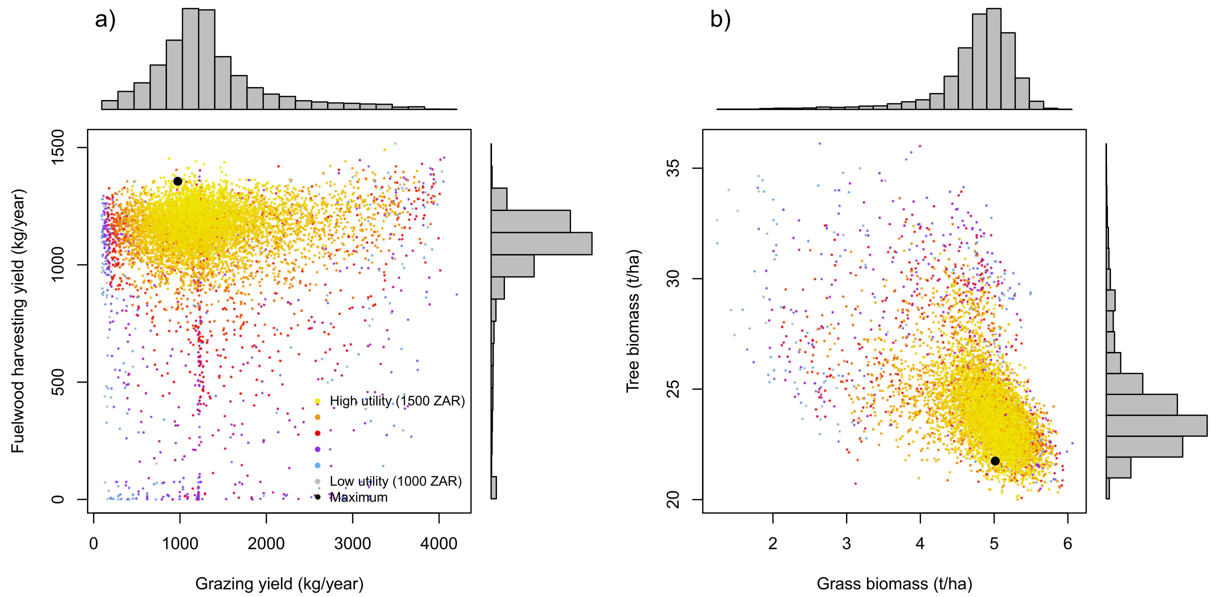

Fig. 5. Grazing and fuelwood harvesting yield (a) and grass and tree biomass (b) for different combinations of the control parameters. Each point indicates one simulation run in the optimization process, colors indicate the utility of stakeholder CB. For state variables (b), points represent the average for the time period between 2046 and 2050.

of the utility. The optimized proportion of animals used for milk production (P_{milk}, Fig. 6b) is close to one, which means that all animals are used for milk production. Reductions of P_{milk} imply reductions of the utility. In contrast, utility is more robust against changes in fuelwood harvesting frequency (f_{fc}, Fig. 6c). Our results indicate that daily fuelwood harvesting is optimal but that less frequent harvesting does not reduce utility considerably. Utility is also sensitive to changes in fuelwood harvesting rate in the planning horizon (I_{fc}, Fig. 6d), with the highest utility when fuelwood harvest is kept almost constant during the entire planning horizon.

3.4. Land-use Impacts on Vegetation Structure

The aDGVM simulates height and stem diameter of individual trees, as well as tree numbers. Climate change induced increases of tree biomass in the baseline scenario (Fig. 3b) can be attributed to increases in the number of tall trees with higher stem diameter (Fig. 7a). In the model, fuelwood harvesting is a function of stem diameter (Fig. 2). Therefore, simulated tree diameter structure is strongly modified by fuelwood collection in the FC and the CB scenarios (Fig. 7b, c). In 2016, trees with small and large stem diameter classes are unaffected by fuelwood collection and similar to the baseline scenario. Intermediate stem diameter classes between 11 and 28 mm, that are preferred for fuelwood harvesting, are depleted (Fig. 7b). Between 2016 and 2050, even larger tree diameter classes (up to 36 mm) become depleted (Fig. 7c) because trees tall enough to be unaffected by fuelwood harvesting grow taller and reach larger diameter classes while recruitment from smaller size classes is not possible due to fuelwood harvesting.

3.5. Changes in the Energy Mix and Recovery – The EMX Scenario

A reduction in fuelwood harvesting in the planning horizon due to changes in the energy mix of households (EMX scenario), allows woody vegetation to recover from utilization. However, recovery is slow both in terms of tree biomass (not shown) and tree population structure (Fig. 8). Recovery occurs mainly in small stem diameter classes and tree numbers in these stem diameter classes are even higher than in the baseline scenario. The number of trees with intermediate stem diameter is still low at the end of the planning horizon in 2050.

3.6. Realistic Land-use Intensities – The REI Scenario

We found substantial differences in the vegetation state and the income between the MAX scenario and the REI scenario with more realistic land-use intensities. Grass biomass is reduced to very low values in the LO REI and CB REI scenarios (Fig. 9a). Woody biomass can benefit from reduced competition by grasses in these scenarios. It exceeds the woody biomass of the baseline scenario in the LO REI scenario while it is similar to the baseline in the CB REI scenario (Fig. 9b). In the FC REI scenario, woody biomass is lower than in the FC MAX scenario due to higher fuelwood harvesting intensities (Fig. 9b). High land-use intensities in the REI scenarios imply that utility is reduced for all three stakeholders, when compared to the MAX scenario (compare Fig. 4b, d, f and Fig. 10a, b, c for LO, FC and CB, respectively, Table 4). While income from grazing is reduced by *ca.* 30%, the income from fuelwood harvesting even gets negative due to over-harvesting of the tree population.

4. Discussion

Rangeland ecosystems in many rural areas are heavily utilized to provide ecosystem services required for subsistence. However, the natural resource base in these areas is not only influenced by land-use but also by climate change. Models aiming at the development of sustainable management strategies for these areas hence need to consider dynamics of the biotic and abiotic environment in combination with the dynamics of socio-economic systems. Here, we present a novel framework that integrates economic models with a complex dynamic vegetation model to investigate management strategies in a rural area in South Africa against the backdrop of climate change. In summary, the model projects that utility of households is maximized if animal numbers are kept below 0.1 animals/ha, animals are used primarily for milk production, and fuelwood is collected almost daily, extracting approx. 1.5 t per year per household. These utilization intensities are, however, much lower than the ones observed in reality. We further show that recovery of the tree population after a policy change towards a reduction in fuelwood harvesting is slow.

Our simulations indicate that the utility from fuelwood collection is maximized when approximately 1.5 t of woody biomass is removed per household and per year. This value is lower than values derived from

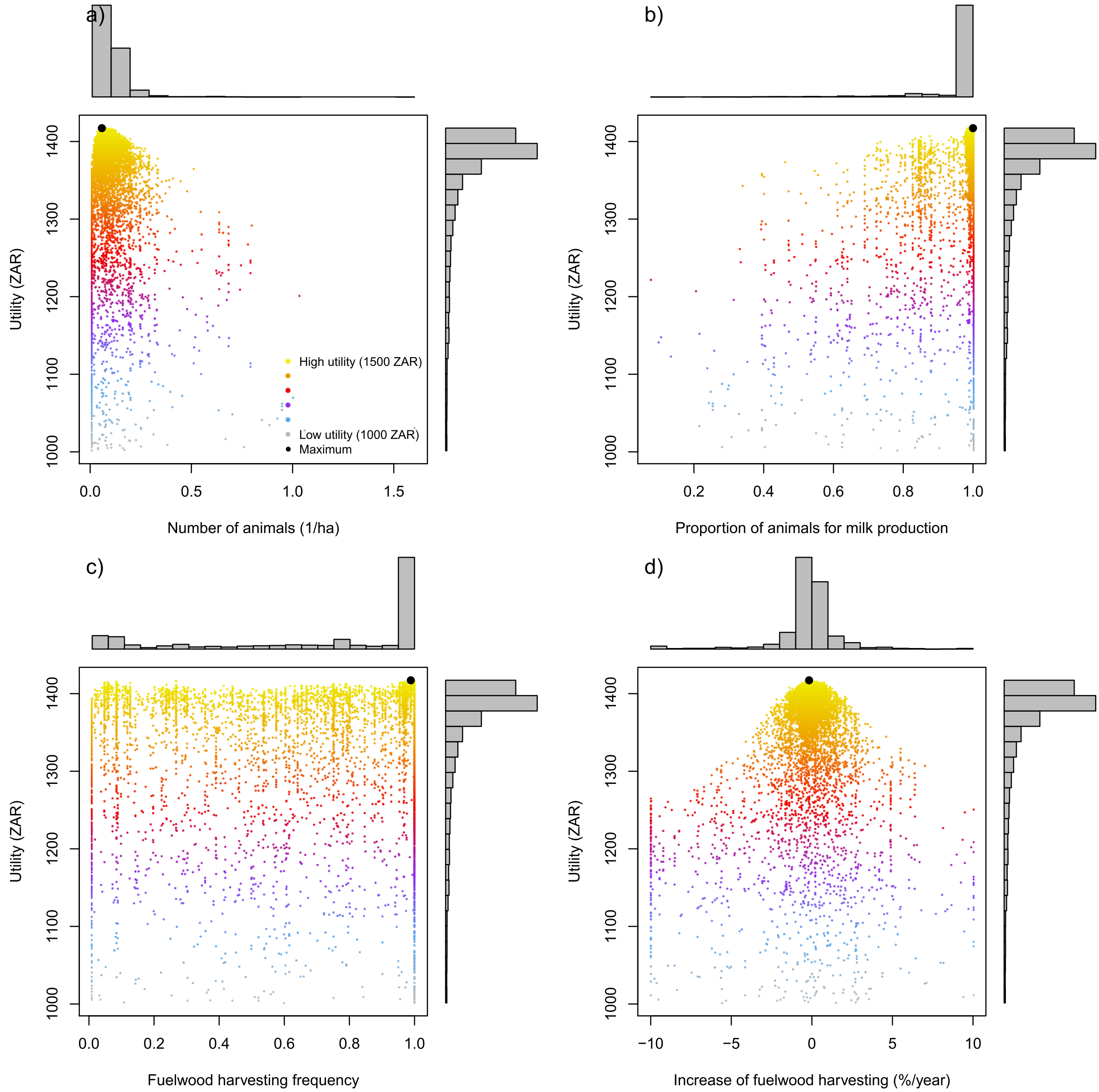

Fig. 6. Sensitivity of utility function to different values of control parameters: (a) Number of animals; (b) proportion of animals used for milk production; (c) fuelwood harvesting frequency; (c) increase in fuelwood harvesting intensity until 20150. Each point indicates one simulation run in the optimization process, colors indicate the utility of stakeholder CB.

household surveys in the study region. Matsika et al. (2013) report fuelwood harvesting of 2.9 t/year for households with electricity and 3.5 t/year for households without electricity. Matsika et al. (2013) reports 3.5 t/year and 4.2 t/year of fuelwood collected per household in Athol and Welverdiend, respectively. We attribute this difference between simulated and observed fuelwood harvesting intensities to the reduction of modeled utility once harvesting demand exceeds biomass supply. This represents a conservative and risk averse utilization strategy that, on the other hand, constrains land-use impacts on vegetation. Under this management strategy, the model simulates a woody biomass reduction of approximately 20% compared to the baseline scenario without land-use. Should we release the constraints on overharvesting, higher yields would be achieved at the cost of lower remaining woody biomass. Maximum fuelwood harvesting in the model is also constrained by the assumption that removal is linked to stem diameter. Once the suitable stem diameter classes are depleted, higher fuelwood harvesting rates are not possible, because the model does not allow stakeholders to adjust by selecting smaller or larger stem diameter classes for harvesting. In reality, it is likely that non-preferred fuelwood size-classes will be harvested once the preferred ones have been depleted or that fuelwood will be collected at more distant areas if possible. In addition, fuelwood collectors may collect less preferred tree species that are, for example, less flammable and with lower energy content.

Utility from livestock is maximized at densities of 0.076 animals/ha and 0.068 animals/ha for the livestock owner and the combined livestock owner and fuelwood collector, respectively. These densities are approximately 10 times lower than observed densities (0.88 animals/ha, Parsons et al., 1997). Similar to fuelwood harvesting, this deviance can be explained by the conservative management strategy in our study that penalizes overgrazing. The model can provide insights how different forms of utilization of the products generated by cattle influence income. Our simulations suggest that yield is maximized if cattle is used primarily for milk production. This is not surprising given that the maximum utility from milk production, G_{milk}^{max}, is higher than the maximum utility of other products considered in this study (except cultural

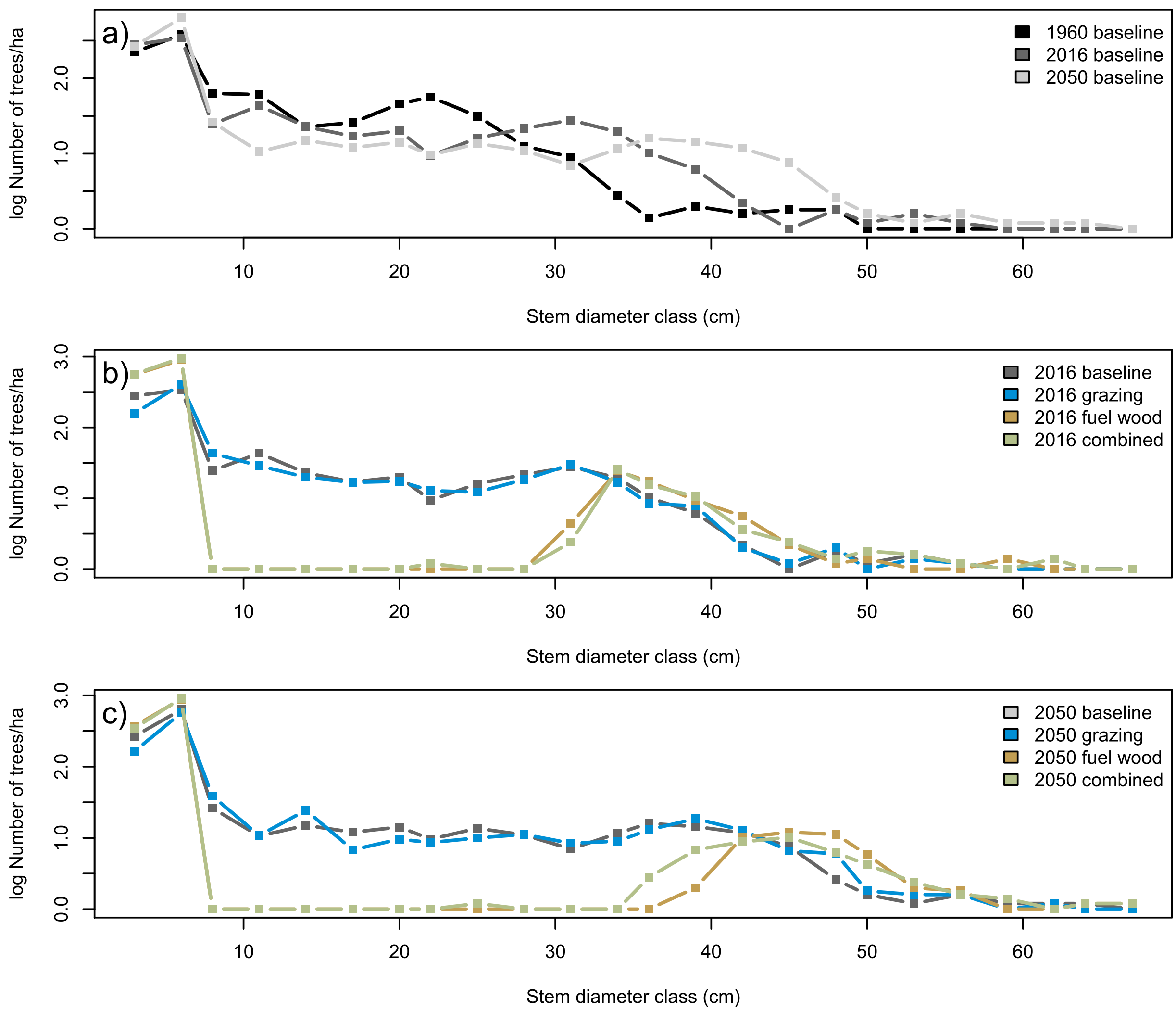

Fig. 7. Impacts of grazing and fuelwood harvesting on the tree population structure. The figure shows the log transformed number of trees in the baseline scenario without land-use in 1960, 2016 and 2050 (a) as well as tree diameter structure in 2016 (b) and 2050 (c) when grazing, fuelwood collection or both activities combined are applied to vegetation.

purposes, but the proportion of animals used for cultural purposes, r_{cult}, is low). In our approach, we did not explicitly consider that cattle is used for multiple reasons, for example that animals producing milk are finally used for meat and leather production.

The deviance between simulated and observed stocking rates and fuelwood harvesting rates exemplifies the tragedy of the commons (Hardin, 1968; Gordon, 1954) that is often prevalent in rangelands with communal tenure. It occurs when several stakeholders utilizing a common resource pool aim at maximizing their individual extraction rates of a resource rather than maintaining sustainable extraction rates

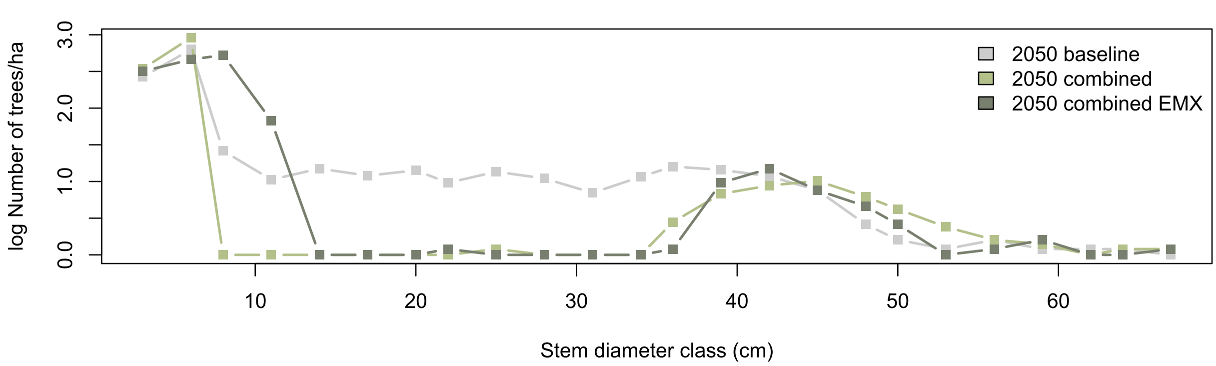

Fig. 8. Recovery of tree population until 2050 in the EMX scenario. In this scenario, fuelwood collection is reduced gradually in the planning horizon such that the fuelwood demand in 2050 is 5% of the demand in 2016. The figure shows the log number of trees in different stem diameter classes and different scenarios in 2050. Here, we only provide results for CB, results for FC are similar.

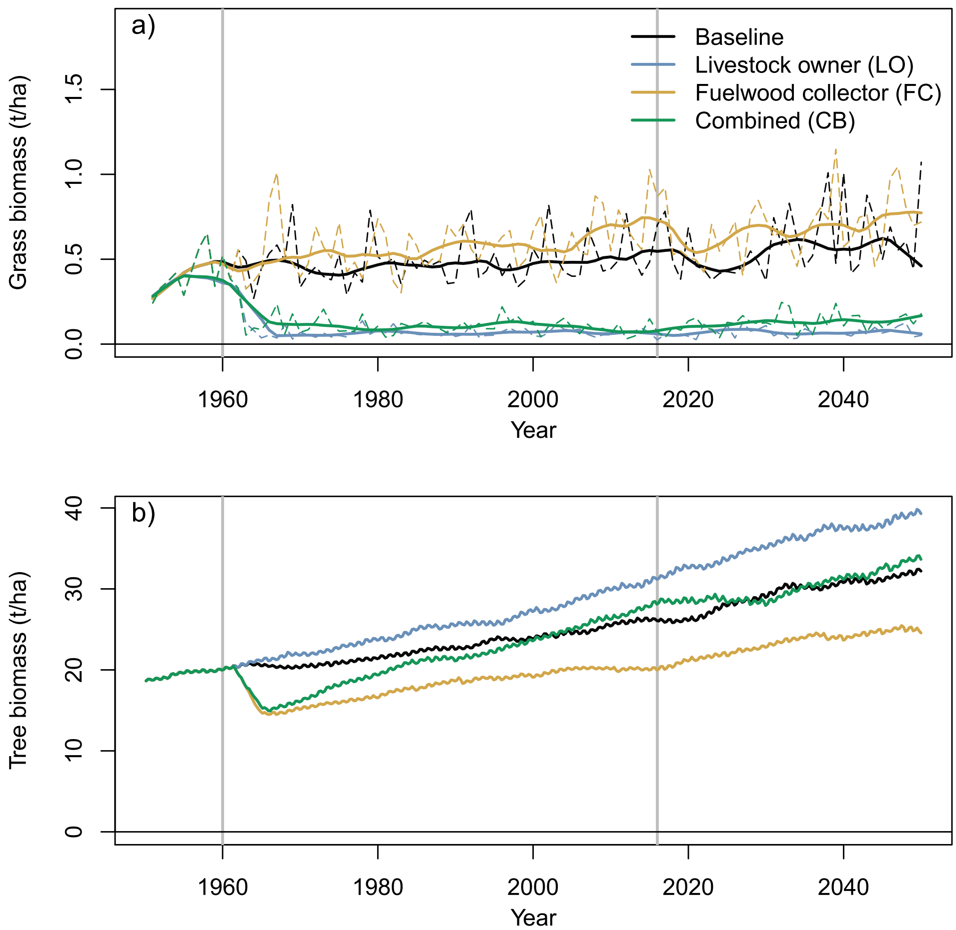

Fig. 9. Impacts of grazing, fuelwood harvesting and combined grazing and fuelwood harvesting on grass (a) and tree (b) biomass in the realistic land-use scenario (REI). For grass biomass, dashed lines represent annual maximum grass biomass values, bold lines represent smoothened time series (locally-weighted polynomial regression). The gray lines indicate the introduction of management in 1960 and the start of the planning horizon in 2016.

that ensure provision of the resource for all stakeholders over longer time scales. We show in our simulations that high and realistic extraction rates are possible and supported by vegetation (REI scenario). Yet, in this situation, vegetation is strongly degraded and the utility calculated by our model is lower than in the MAX scenario where utility is maximized. Both vegetation state and utility of stakeholders would benefit from a reduction of fuelwood extraction and animal stocking rates. To protect and sustain natural resources in communal rangelands, sustainable management strategies are required, for example by planning and application of rotational grazing systems, avoidance of overstocking, fencing, stakeholder dialogue, increasing awareness regarding the sustainable use of resources, and regulating access to resources within communities. Therefore, strengthening local natural resource governance systems that protect both the natural resources and maintain or even improve livelihoods for people should be priority.

In the MAX scenario, wood harvesting yield is slightly higher in simulations with both grazing and fuelwood harvesting than in simulations with fuelwood harvesting only. This difference can be explained by grass-tree interactions. Removal of grass biomass by grazers reduces competitive effects of grasses on trees and thereby promotes tree biomass growth. Higher tree biomass allows higher removal by fuelwood harvesting. However, we did not find strong 'synergy' effects where the utility of fuelwood harvesting and grazing combined exceeds the sum of the utility of fuelwood harvesting and grazing alone because grass-tree interactions are weak in the MAX scenario. Grass-tree interactions influence our results much stronger in the REI scenario. Heavy grazing

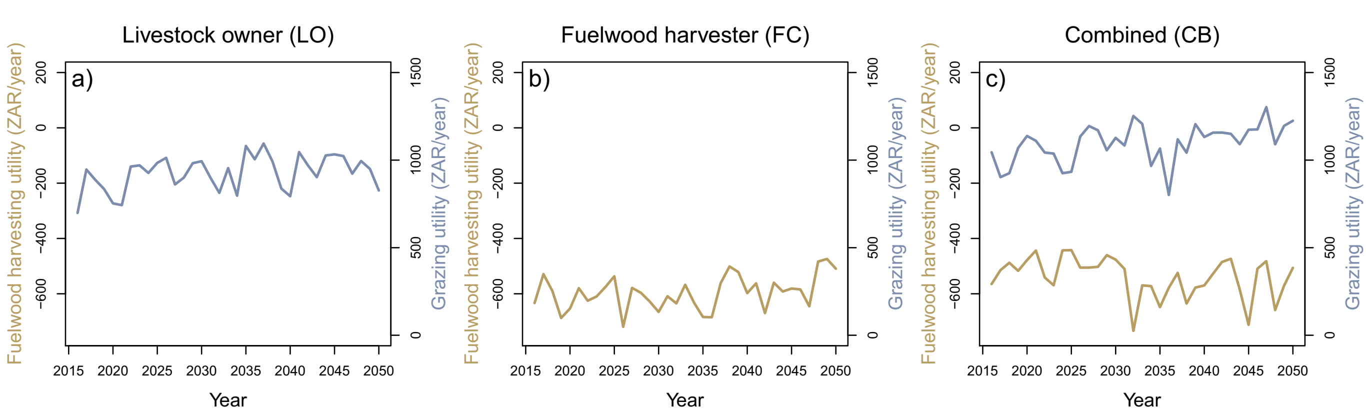

Fig. 10. Impacts of grazing (a), fuelwood harvesting (b) and combined grazing and fuelwood harvesting (c) on utility in the realistic land-use scenario (REI). Note that the scaling of the utility axis differs between fuelwood harvesting and grazing and from scaling in Fig. 4.

allows woody biomass to exceed values of the baseline scenario, even if woody biomass is extracted by fuelwood harvesting. This finding indicates grazing-induced woody encroachment, observed in many savanna systems in southern Africa but also in other savanna regions (Midgley and Bond, 2015; Stevens et al., 2017).

We expected that under future climate conditions, fuelwood harvesting rates would increase due to increased woody biomass production at elevated CO_2 concentrations (Scheiter et al., 2018; Higgins and Scheiter, 2012; Scheiter and Higgins, 2009). However, the rate I_{fc} remained rather stable during the planning horizon (0.12% for fuelwood harvester only, -0.12 % for combined fuelwood harvester and livestock owner), most likely because stem diameter classes utilized for fuelwood collection are depleted at the beginning of the planning horizon (Fig. 7). Higher tree growth rates due to CO_2 fertilization cannot compensate biomass removal. Increasing fuelwood harvesting is therefore not sustainable under the constraint of conservative management, despite climate change effects on woody vegetation.

Recovery of vegetation structure is slow in scenarios where the energy mix of stakeholders, and hence the fuelwood demand, decreases during the planning horizon (EMX scenario). Intermediate tree diameter classes preferred by fuelwood harvesters were removed for more than 50 years prior to the planning horizon and individuals need time to re-establish and re-grow into these depleted diameter classes. Further, we assume that the energy mix changes only gradually such that fuelwood harvesting still occurs during the entire planning horizon and further delays vegetation recovery. These results indicate that long and restrictive resting times are required to allow recovery and restoration of heavily utilized ecosystems. Promoting use of electricity instead of fuelwood seems necessary to ensure vegetation recovery but future research should also consider costs related to the provision and use of electricity.

The presented model provides a powerful framework to investigate interactions between vegetation, climate change and economic aspects of land-use. Nonetheless, we concede that the framework does not represent the full complexity of socio-ecological and economic interactions. For example, in the model, utility of various products as well as market prices are assumed to be constant (Börner et al., 2007). Stakeholders do not dynamically adjust their management decisions to market prices or the vegetation state, for example by selling or buying animals or by switching between different fuel types if necessary. We simply assume that land-use intensity can change by a fixed rate in the planning horizon. The planning horizon was set until 2050 which presumes fully rational decision making. Yet, in reality planning horizons are much shorter and whether the model simulates higher utilization intensities and utilities for shorter time scales remains to be tested. We suggest that an integration of agent-based models into our modeling framework would strongly improve our ability to simulate the dynamic behavior of stakeholders in response to changes in the vegetation state, climate and other socio-ecological drivers (Clemen et al., unpublished).

Further, we do not explicitly consider the spatial settings of a village and how animals and fuelwood collectors move through the landscape. We rather simulate visitations of animals and fuelwood collectors on representative vegetation stands and assume that their resource demand is met elsewhere during the rest of the time. Explicit consideration of movement would influence the timing of visitation events and create utilization gradients in response to the distance to a village. The simulated target area might be impacted several times within a short time and recover during the rest of the year. In contrast, we assume a constant visitation probability during the entire year with short resting times. The village is assumed to be static, i.e. neither the regions used for different forms of utilization nor the human population size in the village change. Increases in human population size would increase pressure on the available resources. Finally, further forms of land-use could be incorporated into the model framework such as crop production, plantations, charcoal production or biodiversity conservation in nature reserves. Such additional stakeholders could represent various external stress factors on rural communities such as changes in property rights or overarching management policies at landscape scale. Such extensions would allow us to apply the model framework in other savanna regions inside and outside South Africa where similar land-use forms and communal land tenures are prevalent.

Recent decades showed massive changes in both land-use and climate, and rates of change are projected to increase in the future (IPCC, 2013, 2014). For a sustainable utilization of natural resources, we therefore require innovative modeling tools that allow us to investigate interactions between social, ecological and economic systems. Our approach is a first step towards the development of such a tool and, despite some limitations, we are convinced that it can contribute to foster discussions between ecologists, economists, conservation managers, decision makers and stakeholders and stimulate interdisciplinary model development.

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